CARBON EMISSIONS AND THEIR INFLUENCE ON INDIA'S HEALTH PROFILE: AN EMPIRICAL ANALYSIS

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Abstract

Environmental degradation caused by rising carbon emissions has emerged as one of the most significant threats to human well-being. This study investigates how carbon emissions influence multiple health-related indicators in India, including health expenditure, fertility rate, per 100K live births, life expectancy, and death rate. Using annual data from the World Bank and Macro trends for the period 2000–2022, the study constructs five bivariate regression models with carbon emissions as the independent variable. In addition, the random walk model and Engel–Granger causality test are applied to determine the stationary properties of the data. Results show that a 1% rise in carbon emissions is associated with a 471.5% increase in health expenditure, an 11.6% reduction in fertility rate, and a 266.27% decline in per 100K live births. Interestingly, life expectancy increases by 72.5%, and death rates decline by 15.65%, indicating mixed outcomes across variables. The findings suggest that although carbon emissions adversely affect maternal and child health indicators, other socioeconomic and medical factors also substantially shape life expectancy and mortality patterns.

Keywords: Carbon Emission, Human Health, Fertility Rate, Health Spending, Life, Per 100K Live, Birth Expectancy, Death Rate, Random Walk Model, Bivariate Regression Model

Introduction:

Natural resources form the foundation of human survival, but rapid industrialization, modern consumption habits, and technological dependency have considerably strained the environment. After India's liberalization policy of 1991, industrial expansion accelerated, drastically increasing energy consumption, pesticide usage, transportation demand, and waste generation. These activities contributed significantly to air, water, and soil pollution—particularly through the accumulation of carbon emissions.

Carbon emissions influence human health directly by deteriorating environmental quality and indirectly through their association with global warming, climate variability, and ecological imbalance. The World Bank estimates that 3.6 billion people live in high climate-risk regions, and climate-related mortality may rise by 250,000 annually between 2030 and 2050. Rising carbon emissions, therefore, represent not only an environmental challenge but also a public health crisis.

Given India's growing population, rapid urbanization, and increasing dependence on fossil fuels, it becomes essential to analyze how carbon emissions affect core health and demographic indicators. This study specifically examines their relationship with health expenditure, fertility rate, per 100K live births, life expectancy, and death rate in India from 2000 to 2022.

Review of Literature

Chaabouni Sami et. al.(2016) investigated the causal relationship between CO2 emissions, health expenditures, and economic development, GDP. The authors have used a global panel of 51 countries from 1995 and 2013 and used dynamic simultaneous-equations and generalized method of moments (GMM) models The results of this study provide a causal relationship between the three variables. Their results show that there is a bidirectional causality between CO2 emissions and GDP per capita, between health spending and economic growth for the three groups of estimates and also show that there is a unidirectional causality from CO2 emissions to health spending, except low income group countries.
The study of Gok et al. .(2018) & Erçelik G (2018) & Modibbo HU (2020) examined the relationship between healthcare expenditure and economic growth. The authors have taken data from 2008 to 2012 in emerging BRICS and MIST countries (Mexico, Indonesia, South Korea, and Turkey). They used moderate effect as a dependent variable; and economic growth and population as independent variable. Authors have used descriptive statistics and multiple

regression models. The analysis results showed that South Korea, Russia, and Brazil were at the top in terms of the efficiency of health expenditures in all years, but South Africa, India and Indonesia were at the lower level. Their study suggested that economic growth could significantly improve health care expenditure.

The study of Zaidi and Saidi (2018) examines the relation between health spending, CO2 emissions, and economic growth. The data has been covered from 1990–2015 Sub-Saharan African nations. The methods/models have used ARDL and VECM Granger causality. The results show the detrimental effects of CO2 emissions on health expenditure. Specifically, 1% increase in CO2 emissions results with a 0.066% decrease in health expenditure. There is an inverse relationship between carbon emissions and health expenditure.

The study of **Muhammad Umar Farooq et al (2019)** titled "The impact of carbon emission and forest activities on health outcomes: empirical evidence from China" investigated the relationship between greenhouse gas emission and human health. Data has been taken from the National Bureau of Statistics of China. Authors have used the panel data of 30 Chinese regisions from 1996 to 2015. The data comprises 600 observations. They have summary statistics and multiple regression models. Results show that significantly more health problems are caused by increases in carbon emissions. Conversely, the activities related to afforestation showed a negative coefficient, indicating that the expansion of forests may be a helpful tool in managing health problems.

The study of **Olufunmilayo T. Afolayan et al (2020)** examined a combined relationship between the carbon emission and health investment on economic development in Nigeria. The data of the time series has been taken for 37 years from the period of 1980-2017 from the World Bank. They have used GDP per capita as a dependent variable, and Physical capital input, human capital, government health expenditure as independent variables. Authors have used the bounds testing approach of the autoregressive distributed lag model and Cobb- Douglas model to investigate the results. Findings show that if 1% increases in the government health investment, the economic development/GDP per capita increases by 0.008%. Corasponding 1% increase in the level of carbon emissions, GDP per capita declines 0.1%. Furthermore, evidence shows that no causal link exists between fossil fuel consumption (FFC) and carbon emissions, and also increased energy consumption directly influences GDP per capita.

The paper of Oluwatoyin A. Matthew et al (2020) examined the relationship among carbon emissions, agricultural output and human health with special reference to West Africa. Data has been covered for the period of 2000 to 2018. The study used the two stage least squares econometric model. The results show that a 1% increase in carbon emissions brings about a 3.818% reduction in agricultural output. It means carbon emissions adversely affect agricultural output in West Africa. 1% increases in carbon emissions bring about a 0.123% increase in life expectancy, that is, carbon emissions have a positive impact on life expectancy in West Africa.

The study of Ruqiya Pervaiz et al (2021) examined the relationship between health expenditures, GDP, human development index (HDI), CO2 emissions (COEM), renewable energy (RENE), financial development (FD) and electricity consumption (EC) using data from 2000Q1 to 2014Q4 for Brazil, India, China and South Africa. The paper applies CIPS and CADF to determine the integration order. The authors used panels dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS) to ascertain the long-run elasticity. The findings from DH confirm a bidirectional causality between HDI and FD. Another bidirectional causal relationship has also been found between FD and EC. The findings of the study also advocate policies in the direction of HDI and health expenditure by adopting RENE.

The study of Sujoy Das and Avijit Debanth (2023) investigated the relationship between life expectancy and carbon emission. The authors have taken data from the world bank for the time period of 1991–2018. They used life expectancy as a dependent variable; and per capita carbon dioxide emission and mean per capita global concentration as independent variables. Authors have used the autoregressive distributed lag (ARDL) test and regression model. Results show that optimum CO2 emission level has been computed as 1.29 metric ton per capita. According to World Bank data, the level of CO2 emission in India has already surpassed 1.99 metric ton per capita in 2017. The results of this study are contradictory from the World Bank. The part of this study is related to our study because authors investigate the impact of carbon emission on human health.

Objective of the Study:

1. To examine the impact of carbon emissions on human health in India by analyzing key health indicators such as health expenditure, fertility rate, life expectancy, and death rate .
2. To analyze the relationship between carbon emissions and maternal and child health outcomes.
3. To assess how rising carbon emissions influence health expenditure in India.
4. To study the effect of carbon emissions on life expectancy and mortality patterns
5. To apply econometric techniques such as bivariate regression, random walk model, and

Engel–Granger causality test to determine the nature and strength of the relationship between carbon emissions and selected health indicators

Source of Data:

The paper focuses on the relationship among the carbon emissions and health spending, per 100K live births, fertility rate, life expectancy and death rate. The data has been taken from the World Bank and Macro trends. The data has been covered for 22 years from the period of 2000 to 2022. The data comprises 132 observations regarding 6 variables (carbon emissions, health spending, per 100K live births, fertility rate, life expectancy and death rate).

Models and Methods:

Methods and models have been used as follow;

1) Random walk model, Engel Grangel casualty test to detect stationary, autocorrelation of the time series data respectively;
2) To examine the relationship between endogenous and exogenous factors by the bivariate regression models.

Following are the bivariate regression models which are given as below;

$CBNEMS_t = \alpha t + \beta\ HELSPND_t + u$……………………………………………..(Equation 1)

$CBNEMS_t = \alpha t + \beta\ LIVBTH_t + u$………………………………………………..(Equation 2)

$CBNEMS_t = \alpha t + \beta\ FRTYRT_t + u$……………………………………………….(Equation 3)

$CBNEMS_t = \alpha t + \beta\ LIFEXCY_t + u$……………………………………………..(Equation 4)

$CBNEMS_t = \alpha t + \beta\ DETHR_t + u$………………………………………………..(Equation 5)

Where is;

1. CBNEMS depicts carbon emissions

2. HELSPND shows heath spending,
3. LIVBTH depicts live birth
4. FRTYRT is fertility rate
5. LIFEXCY depicts life expectancy
6. DETHRT shows death rate
7. t refers to time
8. u depicts random error

Discussion of Empirical Results of Random Walk Model

Dickey Fuller test (Unit Root Test) has been used to deduct to the data set of time series is stationary or non-stationary at all three versions which is given below:

1. $\Delta y_t = \delta x_{t-1}$
2. $\Delta y_t = \alpha + \delta x_{t-1}$
3. $\Delta y_t = \alpha + \delta x_{t-1} + ƁT$

If the value of coefficient is less than one and significant then time series of data to be taken as stationary, which is given below:

$\sigma = 1 - Ɓ, = 1 - 0.5, = 0.5 < 1$

The value of coefficient is significantly less than 1, the series to be taken as stationary.

$\sigma = 1 + Ɓ = 1 + 0.5 > 1$

If value of coefficient is greater than one and significant then the series is non-stationary.

$\sigma = 1 + Ɓ = 1 + 0.5 = 1.5$

If the coefficient 0.5 is not significant, it is as good as 0 has the root converge to 1 series is non-stationary it is said to be in unit root circle.

The value of coefficient must be significantly negative and less than one for the stationary time series.

Table 1 analyses the empirical results of RWM for testing stationary and non-stationary series of data.

Table - 1

Health Expending (Per Capita)	Equation - 1	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	0	NA		
	Health Expending	47.97	21.82	1+47.97	48.97>1
	Equation - 2	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	56.74	122.15		
	Health Expending	7.25	21.13	1+7.25	8.25>1
	Equation - 3	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	67.71	91.26		
	Health Expending	-0.31	-15.07	1+(-0.31)	0.69<1
	Time	1.51	3.84		
per 100K Live Births	Equation - 1	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	0	NA		
	per 100K Live Births	135.69	6.14	1+135.69	136.69>1
	Equation - 2	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	560.06	22.99		
	per 100K Live Births	-266.27	-14.81	1+(-266)	-265>1
Fertility Rate	Equation - 1	Coefficients	t statistic	ρ = 1+β	ρ <1

	Intercept	0	NA		
	Fertility Rate	1.86	11.38	1+1.86	2.86>1
	Equation - 2	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	4.21	60.24		
	Fertility Rate	-1.16	-22.49	1+(-1.16)	-0.16>1
Life Expectancy	Equation - 1	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	0	NA		
	Life Expectancy	47.98	21.82	1+47.98	48.98>1
	Equation - 2	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	56.74	122.16		
	Life Expectancy	7.25	21.14	1+7.25	8.25>1
	Equation - 3	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	67.71	91.26		
	Time	-0.31	-15.01		
	Life Expectancy	1.52	3.85	1+1.52	2.52>1
Death Rate	Equation - 1	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	0	NA		
	Death Rate	5.48	14.40	1+5.48	6.48>1
	Equation - 2	Coefficients	t statistic	ρ = 1+β	ρ <1
	Intercept	9.80	65.73		
	Death Rate	-1.56	-14.14	1+(-1.56)	-0.56>1

Source: Author's own calculations

The table shows that

1. The time series of health expending on the two equations is non-stationary since the roots of the equations are greater than one, but the negative coefficients of the lagged health expending is statistically significant. Hence roots of the equations of health expending on the equation three is less than one. Therefore, the time series of health expending is stationary.
2. The time series of per 100K live births on the first version of RWM is non-stationary since the roots of the equations is significantly greater than one, but the negative coefficient of per 100K live birth is statistically significant on the equation 2. It means the coefficient is less than zero. Therefore, the time series of per 100K Live Births is stationary.
3. The time series of Fertility Rate on the first equations is non-stationary since the roots of the equations is greater than one, but the negative coefficients of the Fertility Rate on second equation is statistically significant. Hence root of the equation of fertility Rate on the equation 2 is less than one. Therefore, the time series of Fertility Rate is stationary.
4. The positive coefficient of the time series of life expectancy on the all three versions is non-stationary since the roots of the equations are greater than one.
5. The time series of death rate on the first equations is non-stationary since the root of the equation is greater than one, but the negative coefficient of the death rate is statistically significant on the equation 2. Therefore, the time series of death rate is stationary.

On the basis of the above results, it may be inferred that the time series of **life expectancy** is not stationary. Therefore, The results furnished by the regressions involving **life expectancy** required validation by Engel – Granger test (Gujarati, 2013). Engel – granger test hypothesized that even if a regression involves non-stationary time series of one or more variables, the linear combination of variables in the regression may still be stationary provided that the variables are well co-integrated in the equation. Co-integration of the variables in a regression is examined by the application of the Engel – Granger test.

Discussion of Empirical Results of OLS bivariate regression models

Table 2 comprises the empirical results of OLS bivariate regression models. Table shows that the degree and direction of carbon emissions which is effect on the several five variables namely health spending, per 100K live births, fertility rate, life expectancy and death rate.

Table – 2

Health Expending (Per Capita)	Coefficients	t Stat.	R^2	F	Significance F
Intercept	-20.23	-7.87	0.974	617.11	0.000001
CBNEMS	47.15	24.84			
Per 100K Live Births	Coefficients	t Stat.	R^2	F	Significance F
Intercept	560.07	23.00	0.925	219.34	0.00001
CBNEMS	-266.27	-14.81			
Fertility Rate	Coefficients	t Stat.	R^2	F	Significance F
Intercept	4.21	60.25	0.966	506.08	3.72E-15
CBNEMS	-1.16	-22.50			
Life Expectancy	Coefficients	t Stat.	R^2	F	Significance F
Intercept	56.74	122.16	0.963	446.90	0.00000
CBNEMS	7.25	21.14			
Death Rate	Coefficients	t Stat.	R^2	F	Significance F
Intercept	9.80	65.73	0.916	199.90	1.6E-11
CBNEMS	-1.56	-14.14			

Source: Author's own calculations

Table – 2 shows that:

1. The regression function for all the five models (namely for health spending, per 100K live births, fertility rate, life expectancy and death rate) fit the data well.
2. The significant coefficients of determination for all five models are 0.974, 0.925, 0.996, 0.963 and 0.916 respectively. Thus, the functions explain 97.4%, 92.5%, 99.6%, 96.3% and 91.6% of the total variation of the models over the years.
3. Corresponding 1% increasing in carbon emission, the health spending increases by 471.5%. It means health expenses hugely affected with carbon emissions. But the negative coefficient of intercept is statistically significant. It means the function influence with other variables which are not included in this model.
4. If the 1% increasing in carbon emissions, per 100K live births decreases by 266.27%. It may be inferred that the carbon emission decreases the per 100k live birth rate at a huge level.
5. Corresponding 1% increasing in carbon emissions, the fertility rate decreases by the 11.6%. It means carbon emission harms the fertility rate of the women.
6. If 1% increasing in the carbon emissions, the life expectancy increases by the 72.5%. It means the human life is not affected only by the carbon emissions. It may be inferred that the life expectancy hugely affected by other factors; communicable and non- communicable diseases (flu, corona virus and cancer, high blood pressure, diabetes high cholesterol level, and obesity etc. respectively) and other socioeconomic factors like too much and low sleep, sitting too much, lack of social interactions, anxiety and depression, work stress, junk and fast food, fruits and vegetables containing chemical and pesticides, huge use of computer screen smoking and alcoholic drinks etc.
7. Corresponding 1% increasing in carbon emissions, the death rate decreases by 15.65%. It means the death rate is not only affected by the carbon emissions. It may be included all the above factors which is mentioned in point number sixth.
8. The positive coefficients of intercepts for per 100K live births, fertility rate, life expectancy and death rate are statistically significant. Thus, it may be inferred that these functions are affected by other variables not only carbon emissions.

However, the perusal of the study shows that if the carbon emissions increase then the health expenses increase and, per 100K live births and fertility rate decrease. But carbon emissions affect to the life expectancy positively. With the increase of carbon emissions life expectancy also increase and death rate decrease with it. Thus, the study provides the results of mix beg.

Findings and Conclusion of the study

The results of the study show that the health spending increases with the carbon emissions by 471.5% since carbon emission hugely affected to the human health. Our findings also ensure that per 100K live birth and fertility rate of women decreases with the carbon emissions increase. But results also contradict in the case of life expectancy and death rate. The results of regression functions show that the life expectancy increases with carbon emissions and death rate decrease. The findings of the study are mix bag. It may be inferred that the carbon emissions also affect the human health but as well as there are lot of factors which are greatly affect to the human health.

Recommendations and Policy implications of the empirical study

Therefore, the study recommends the followings for the government to the formulate policies for the environment and, human to take some important precautions in their daily routine.

1. **For the government -** environmental policies should be formulated with a special preview of government bodies for the growth of agricultural and industrial sectors to increasing the productivity in the both sectors rather than the policies of growth and development should not harm to the environment and human health. Government should take major initiatives to improve health facilities and provide at low price rate to the common people for reducing death rate, health spending, and increasing to live birth rate, fertility rate of women and life expectancy of human. Government should increase health expenditure for the innovation and invented new technology in medical field. Government should encourage to the farmers to produce organic fruits, vegetables, pluses, wheat, paddy/rice and other food grains and also aware to the people to consume organic food grains rather than containing chemical and pesticides by introducing policies.
2. **For the human –** people should take some precautions in day to day life. People should take a good sleep for 7-8 hours in a day and try to be socialized to people and their surroundings. People should not take depression and work stress and avoid, junk and fast food, fruits and vegetables containing chemical and pesticides, huge use of computer screen smoking and alcoholic drinks etc. Everybody has to be contribute to the save environment by the planting new trees and throw their garbage at the define places.

References:

1. Muhammad Umar Farooq et al, “The impact of carbon emission and forest activities on health outcomes: empirical evidence from China” , Environmental Science and Pollution Research, 2019.
2. Olufunmilayo T. Afolayan et al, “Carbon Emissions, Human Capital Investment and Economic Development in Nigeria”, International Journal of Energy Economics and Policy, Vol 10 , Issue 2, 2020.
3. Sujoy Das and Avijit Debanth, **“** Impact of CO2 emission on life expectancy in India: an autoregressive distributive lag (ARDL) bound test approach” , Future Business
   Journal volume 9.issue 5, 2023
4. Ruqiya Pervaiz et al, “Do health expenditure and human development index matter in the carbon emission function for ensuring sustainable development? Evidence from the heterogeneous panel”, Air Quality, Atmosphere & Health, volume 14: page no. 1773–1784, 2021
5. Chaabouni Sami et. al, “On the causal dynamics between CO2 emissions, health expenditures and economic growth.” Sustainable Cities and Society, Volume 22, page no. 184-191 -
6. Zaidi & Saidi, “Environmental pollution, health expenditure and economic growth in the Sub-Saharan Africa countries: panel ARDL approach”. Sustain Cities Society, volume 41:page no.833–840,2018
7. Oluwatoyin A. Matthew et al, “Carbon Emissions, Agricultural Output and Life Expectancy in West Africa", International Journal of Energy Economics and Policy, Vol 10, Issue 3, 2020.
8. Gok MS, Ongel V, Altindag E. Analysis the interplay between economic growth and health expenditures: the case of emerging economies. *J Global Strat Manage.* (2018) 12:53–62. 10.20460/JGSM.2019.268.
9. Erçelik G. The relationship between health expenditure and economic growth in Turkey from 1980 to 2015. *J Polit.* (2018) 1:1–8.
10. Modibbo HU, Saidu AM, “Health expenditure and economic growth nexus: a generalised method of moment approach for the case of selected Africa countries”. *Lapai J Econ.* (2020) vol. 4, page. 12–21.